NORWEGIAN SCHOOL OF ECONOMICS

An Empirical Estimation of the Default Risk of Chinese Listed Company Based on the Merton-KMV Model

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"This thesis was written as a part of the master program at NHH. Neither the institution, the supervisor, nor the censors are - through the approval of this thesis - responsible for neither the theories and methods used, nor results and conclusions drawn in this work."

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Abstract

This paper calculates the "Default Likelihood Indicators" (*DLI*) for Chinese listed companies by using the Merton-KMV model during the period from 2000 to 2010 and examines the predictive power the of the Merton-KMV model. We construct some logit regression models and regress the indicator of default on *DLI* and other variables that may be important in predicting default. The results reveal that Merton-KMV is a significant model to predict default in Chinese market, however it is not a sufficient model since we can improve the predictive performance of the Merton-KMV model by adding financial ratios measuring profitability, leverage and liquidity. In addition, it is found that the functional form of the Merton-KMV model adds value to that of the inputs for the model. Finally we draw the power curve for the Merton-KMV model, the pure accounting model and a hybrid model that combine *DLI* calculated from the Merton-KMV model and financial ratios measuring profitability, leverage and liquidity. We find that the hybrid model outperforms the other two models and the accounting model is the weakest one.

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1. Introduction

Due to the recent global financial crisis which triggers a great number of corporation defaults (Moody's, 2009), as well as the innovation in the corporate debt and derivative products, both academics and practitioners have shown renewed interest in default risk modeling. One of the most frequently studied forecasting models is the Merton-KMV model, which is derived from the ground-breaking work of Merton (1974) and its most successful commercial variant - KMV model.

The original Merton model argues that corporation defaults occur when the value of the firm's assets fall below a certain threshold (the default point), more specifically, the book value of the firm's debt (Tudela & Young, 2005). With the simplifying assumption that a firm only consists of equity and zero-coupon debt and that the firm's asset value is log normally distributed, the original Merton model provides a clever method to calculate the market value as well as the risk of the firm's claims by viewing the equity of the firm as a call option on the underlying value of the firm with a strike price equaling to the face value of the firm's debt. The KMV model invented by KMV Corporation[1] in 1993 is one of the most successful commercial variants of the Merton model. The most critical contribution of the KMV model to the original Merton model is its relaxing some simplifying assumptions that are violated in practice. The KMV model applies the framework of the Merton model to identify the "Distance to Default" (*DD*) of the firm and then translates it to the "Expected Default Frequency" (*EDF*) by using a proprietary database[2], which obtains the relationship

[1] Moody's purchased KMV Corporation in February 2002 and merged it with Moody's Risk Management Service (MRMS) to create Moody's KMV. In this paper, the terms KMV and Moody's are used respectively to refer to KMV Corporation and Moody's before this acquisition took place.

[2] "The database includes over 250,000 company years of data and over 4,700 incidents of default or bankruptcy. From this data, a lookup or frequency table can be generated which relates the likelihood of default to various levels of distance-to-default. For example, assume that we are interested in determining the default probability over the next year for a firm that is 7 standard deviations away from default. To determine this EDF value, we query the default history for the proportion of the firms, seven standard deviations away from default that defaulted over the next year. The answer is about 5 basis points (bp), 0.05%, or an equivalent rating of AA."—Moody's (2003).

between *DD* and *EDF* from data on historical default and bankruptcy frequency. However, due to the fact that the database is propriety information, dozens of academic researchers establish a "feasible" KMV-like model (we call it Merton-KMV model in this paper), which captures the framework of the original Merton model and some of the technical details from KMV model, to generate the default risk of the firms and examine the predictive power of this Merton-KMV model[3].

This paper is trying to calculate the "Default Likelihood Indicators" (*DLI*)[4] for Chinese listed companies by using the Merton-KMV model and identify the predictive power of the Merton-KMV model by using data of Chinese listed companies. There are four important reasons to do so.

First, the new Enterprise Bankruptcy Law became effective since June 2007. With the enforcement of the new Enterprise Bankruptcy Law, the development for bankruptcy process for firms in China is expected to create a huge impact (Altman, Zhang, & Yen, 2007). Therefore it is important to identify the financial distress for listed firms thus give an early warning to relevant stockholders.

Second, although considerable researches have been carried out, previous researches that put efforts forward modeling risk focus on the developed market, in other words, little attention has been paid to developing market, such as Chinese market, despite the fact that Chinese financial market has been playing an increasingly significant role in recent years with the ever-elevating globalization and integration of the world's economy. This paper is trying to geographically enrich the research in default risk

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[3] Examples include Crosbie and Bohn (2003), Vassalou and Xing (2004), Tudela & Young (2005), Patel and Vlamis (2007), Bharath and Shumway (2008), and etc. We will further discuss the empirical studies and the detail of the models in the following section.

[4] Vassalou and Xing (2004) argue that strictly speaking, the so called "Probability of Default" derived from the Merton-KMV model is not a default probability because "it does not correspond to the true probability of default in large samples. In contrast, the default probabilities calculated by KMV are indeed default probabilities because they are calculated using the empirical distribution of defaults. For that reason, we do not call our measure default probability, but rather default likelihood indicators (DLI)". Following Vassalou and Xing (2004), we call the measure of default probability from the Merton-KMV model as DLI in this paper.

modeling by taking the empirical studies in Chinese market.

Third, most of the previous studies conducted by Chinese researchers define defaulted firms as "PT"[5] firms or "ST"[6] firms. "ST" firms refer to the domestic listed companies with the stock losses for two consecutive years[7]. To better protect investors, China's Securities Regulatory Commission (CSRC) decided in March 1998 to differentiate those firms in financial difficulties by launching a new policy to offer "ST" to such firms. "PT" firms refer to the domestic listed companies with the stock losses for three consecutive years[8]. Since July 9, 1999 Shanghai and Shenzhen Stock Exchange have implemented special transfer service for such kind stocks and named them "PT". Intuitively using the accounting model (or just the accounting ratio alone) rather than the Merton-KMV model, an equity market based model, is the most efficient way to predict defaults. In other words, there is no need to use the more complex Merton-KMV model to differentiate the "ST" firms or "PT" firms from healthy firms as the previous studies do. In this paper, default firms are defined as delisted firms. Although the law does include bankruptcy as one possible solution to resolve distress, liquidation and asset possession rarely happen in China as they do in America. In fact, no listed firms have ever been actually filed for bankruptcy before 2010 in China. Being delisted in China is in fact equivalent to going bankruptcy.

Fourth, different from relevant studies in developed market, most of the previous studies conducted by Chinese researchers choose a small study sample for their researches. The relative small sample makes the results less convincing. In this paper, the full list of the companies that alive in 2010 and issue A-shares[9] in Shanghai and

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[5] PT is short for Particular Transfer.

[6] ST is short for Special treatment

[7] Companies have negative cumulative earnings over two consecutive years or net asset value (NAV) per share below par value (book value).

[8] Companies have negative cumulative earnings over three consecutive years or net asset value (NAV) per share below par value (book value).

[9] A-shares are specialized shares of the Renminbi currency that are purchased and traded on the Shanghai and Shenzhen stock exchanges. This is contrast to B-shares which are owned by foreigners who cannot purchase A-shares due to Chinese government restrictions. Since A-shares better represent the Chinese market, we just

Shenzhen Stock Exchanges are studied and the study period stretches from 2000 to 2010. This is supposed to make the results more plausible. However due to the data availability as well as the fact that there are very few defaults in China compared with those in America, our studies include a relative small number of defaults. This may influence our results to some extends.

Following Bharath & Shumway (2008), this paper assesses both the reliability and efficiency of the Merton-KMV model. The reliability of the Merton-KMV model in predicting default is tested by regressing the indicator of default on the "Default Likelihood Indicators" (*DLI*)" calculated from the Merton-KMV model. The efficiency of the estimation is examined by testing whether the predicting power of the Merton-KMV model can be improved by adding other variables[10].

This paper reveals that generally the annual aggregate "Default Likelihood Indicators" (*DLI*), defined as a simple average of the *DLI* of all firms, is lower in China than that in America. In addition, it is found that the Merton-KMV is a significant method to predict default in Chinese market. However the Merton-KMV is not a sufficient method since we find that we can improve the performance of the Merton-KMV model by adding some accounting variables. Moreover the functional form of the Merton-KMV model adds value to that of the inputs for the model. These findings are in line with those revealed by Bharath & Shumway (2008). Finally we draw the power curve for the Merton-KMV model, the pure accounting model and a hybrid model that combine *DLI* calculated from the Merton-KMV model and financial ratios measuring profitability, leverage and liquidity. We find that hybrid model outperforms the other two models and the accounting model is the weakest one.

The remainder of this paper is organized as follows. Section 2 presents the literature review of the theoretical development on Merton-KMV model and some recent relevant empirical studies. Section 3 gives brief introduction of Chinese institutional

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include A-shares in our sample.

[10] The details of the method are showed in section 4.

background. Section 4 outlines the methodology that will be used in this paper, as well as the sample and data selection criteria. Section 5 describes the data on Chinese listed companies. Section 6 discusses the results. Finally the paper will be wrapped up by the conclusions in section 7.

2. Literature review

The Merton-KMV model is in essence an equity market based model, the calculations of which use publicly available information on equity market. Other default risk models include accounting models and bond market based models. In this section, the framework and development of the Merton-KMV model will be presented. This is followed by a brief introduction of the accounting models and bond market based models as well as the comparison between the equity market based models and the other two types of models. Finally some recent empirical studies that are close to this paper will be given.

2.1 The framework and development of the Merton-KMV model

2.1.1 The Merton model

The Merton model is a very clever application of classic financial theory (Bharath & Shumway, 2008). Merton (1974) argues that the equity of a firm can be viewed as a call option on the firm's assets with the exercise price as the value of the firm's debt so that we can apply the Black-Schole option pricing formula to calculate the value of firm's claims. All his deduction is based on the following two simplifying but salience assumptions:

1) The total value of the firm's asset follows geometric Brownian motion

$$\frac{dA_t}{A_t} = \mu \cdot dt + \sigma_A dZ_t \tag{2.1.1.1}$$

where A_t is the value of the firm's assets on any date t, with an instantaneous drift μ and an instantaneous volatility σ_A, and Z_t is a standard Wiener process.

2) The firm only has equity and a single issue of zero-coupon debt with face value of F and maturity T in its capital structure.

Based on the assumptions mentioned above, Merton (1974) shows that the equity of the firm can be modeled as an option on firm value with the strike of F and maturity T. The underlying logic is quite simple. If A_T exceeds F on date T, equityholders will receive the amount of (A_T - F). Otherwise, i.e. $A_T < F$, equityholders will receive nothing. The payoffs received by equityholders at time T thus can be written as

$$max\{A_T - F, 0\} \qquad (2.1.1.2)$$

where A_T is the value of the firm's assets on date T (the maturity of the firm's debt), F is the face value of the firm's debt. It is clear that (2.1.1.2) is exactly the payoffs from longing a call option on the firm's assets with the strike of F and maturity T. Referring to the Black-Scholes pricing formula, the value of the equity price can be written as

$$E_t = A_t \cdot N(d_1) - e^{-r(T-t)} \cdot F \cdot N(d_2) \qquad (2.1.1.3)$$

where E_t is the market value of the firm's equity on any date t, r is the riskless interest rate, and $N(\cdot)$ is the cumulative distribution function of the standard normal distribution. d_1 and d_2 in this equation is given by

$$d_1 = \frac{ln\left(\frac{A_t}{F}\right)+\left(r+\frac{\sigma_A^2}{2}\right)(T-t)}{\sigma_A\sqrt{T-t}} \qquad (2.1.1.4)$$

$$d_2 = d_1 - \sigma_A\sqrt{T-t} \qquad (2.1.1.5)$$

Since that the equity of the firm can be viewed as a call option on the firm's assets, the observable volatility of the equity can be expressed as a function of the unobservable volatility of the firm value from Ito's lemma and it is showed as

$$\sigma_E = \frac{A_t}{E_t} \cdot N(d_1) \cdot \sigma_A \tag{2.1.1.6}$$

where σ_E is the volatility of the firm's equity, $N(d_1)$ is the hedge ratio from (2.1.1.3).

Given (2.1.1.3) and (2.1.1.6), the value and volatility of the firm's underlying assets can be calculated from the observable variables—E_t, σ_E, F, T and r.

Similarly, the firm's outstanding debt can be modeled as a portfolio of longing a default-risk-free zero coupon bond with face value of F and shorting a put option on the firm's asset with the exercise price of F. The payoffs received by debtholder at time T thus can be written as

$$F - max\{F - A_T, 0\} \tag{2.1.1.7}$$

The expression above can be divided into two parts, respectively F and $-max\{F - A_T, 0\}$. The former term equals to payoffs from longing a riskless bond with the face value of F and maturity T while the latter term is the payoffs from shorting a put option on the firm's with exercise price of F and maturity T. With such decomposition, the valuation of the firm's debt can then be transformed into pricing the riskless bond and the put option

$$B_t = F \cdot e^{-r(T-t)} \tag{2.1.1.8}$$

where B_t is the value of the riskless bond with face value of F and maturity T on any date t. In addition, the value of the put option can be obtained from the Black - Scholes pricing formula

$$P_t = e^{-r(T-t)} \cdot F \cdot N(-d_2) - A_t \cdot N(-d_1) \tag{2.1.1.9}$$

P_t is the value of the put option on the firm's asset with the exercise price of F and maturity T on any date t.

Given (2.1.1.2), (2.1.1.3) and (2.1.1.4), the value of the firm's debt can be expressed as follows

$$D_t = B_t - P_t = F \cdot e^{-r(T-t)} - \left\{ e^{-r(T-t)} \cdot F \cdot N(-d_2) - A_t \cdot N(-d_1) \right\} \qquad (2.1.1.10)$$

D_t is the value of the firm's debt with face value of F and maturity T on any date t. The implied value of A_t and σ_A from (2.1.1.3) and (2.1.1.6) can then be translated into the value of the firm's debt (D_t) by using (2.1.1.10).

2.1.2 Some extensions of the Merton model in academic field

The framework of the ground-breaking work by Merton booms the development of the default risk modeling. This branch of default risk modeling is known as "structural models"[11] and can be divided into two categories, respectively exogenous default models and endogenous default models. In exogenous default models, default happens whenever the assets' value falls below a default boundary. While in endogenous models default is chosen by management to maximize equity values.

Examples of exogenous default models include Longstaff and Schwartz (1995), which argue that default happens when the value of firm's assets falls below an exogenous default boundary, which depends on the face value of the debt (Patel & Pereira, 2007). Different from the Merton model, which assumes the short-term riskless interest is constant, Longstaff and Schwartz (1995) argue that the short-term riskless interest rate is a stochastic process that converges to long-term riskless interest rate and it is negatively correlated to asset value process. In addition, Longstaff and Schwartz (1995) take the bankruptcy cost into consideration.

Endogenous default models were introduced by Black and Cox (1976). In endogenous

[11] Another branch of default risk predicting models are called as reduced form models. Different from the structure models which argue that a firm defaults when its asset value drops to its debt value, reduced form models view the default of a firm as an event that happens unexpectedly and this branch of models are inspired by the work of Jarrow and Turnbull (1995).

default models, equityholders face the tradeoffs between keeping the equity "alive" and paying for the debt holders. If the value of firm's assets exceeds the default boundary, equityholders will choose to keep the firm running and paying the debtholders, otherwise they will choose default. The default boundary is determined not only by debt principal, but also by the riskiness of the firm's activities (as reflected in value process), the maturity of debt issued, payout levels, default costs, and corporate tax rates (Leland, 2004).

2.1.3 The Merton-KMV model

In addition to the great development in the academic area, experts in commercial area have made a remarkable progress concerning the default risk measurement inspired by Black and Scholes (1973) and Merton (1974) since 1990s. KMV model released by KMV Corporation in 1993 is one of the most outstanding achievements. KMV model estimates the default of a firm according to a three-step procedure: 1) estimate the current market value and the volatility of the firm's assets; 2) determine the "Distance to Default" (*DD*); 3) scale the *DD* to "Expected Default Frequency" (*EDF*). The most significant contribution of the KMV model is its construction of a database that showing the relationship between *DD* and the *EDF* from observing the US company histories. The *EDF* of the firm with a specific *DD* can be obtained by referring to the database. However due to the fact that the database is propriety information, some academic researchers establish a "feasible" KMV-like model to illustrate some of the technical details of estimating the *EDF*. The details of the calculation are as follows.

First, calculate the market value and the volatility of the firm's assets. The market value and the volatility of the firm's assets can be calculated by solving (2.1.1.3) and (2.1.1.6) as showed above. However most of the empirical studies[12] argue that "the relationship between σ_E and σ_A from (2.1.1.6)) holds only instantaneously, and in

[12] see Crosbie and Bohn (2003), Vassalou and Xing (2004), Patel and Vlamis (2007), Bharath and Shumway (2008), and ect..

practice, the market leverage moves around far too much for (2.1.1.6)) to provide reasonable results". To solve the problem, an iterative procedure is usually introduced as follows.

Step 1: Propose a start guess value of σ_A, and use this value to extract A_t from (2.1.1.3).

Step 2: Calculate the log return on assets using A_t extracted in the previous step, and derive σ_A and μ using the log return on assets.

Step 3: Repeat step 1 and step 2 until convergence is achieved.

Second, identify the "Default Point" (*DP,* which is the same to ***F*** mentioned above**).** Vassalou & Xing (2004) argue that "the interest payments of the long-term debt are parts of short-term liability. In addition, the size of the long-term debt affects the firm's ability to roll over its short-term debt, and therefore reduce the default risk." Thus it is very important to include long-term debt in the calculation. Following KMV, the *F* is usually be defined as

$$F = STD + 0.5LTD \quad (2.1.3.1)$$ [13]

where *F* is the Default Point, *STD* is the short-term debt and *LTD* is the long-term debt. This setting is based on KMV Corporation's empirical observation and it is argued that the choice of using 50% of the log-term debt is sensible and captures adequately the financing constrains of firms.

Third, deduce the "Probability of Default" (or *EDF* in KMV model). With the implied market value and the volatility of the firm's assets from the iterative calculation above, and the *F* from (2.3.1), the "Probability of Default" (or *EDF* in

[13] Vassalou and Xing (2004) demonstrate that they examined the variation of the ratio long-term debt to total debt across size and BM quintiles. The results show that overall speaking the difference in the ratios is not deem large enough to alter the qualitative results (Vassalou & Xing, 2004). Thus in this paper, we use (2.1.3.1) to derive the face value of the firm's debt.

KMV model) can be written as follows

$$DLI_t = Pr\{A_t \leq F|A_0 = A'\} = Pr\{lnA_t \leq lnF|A_0 = A'\} \tag{2.1.3.2}$$

DLI_t is the "probability of default" by time *t*, A' is the market value of the firm's assets at time *t*, and *F* is the face value of the firm's debt which expires at time *t* and can be calculated from (2.1.3.1) above. Vassalou and Xing (2004) argue that strictly speaking, the so called "Probability of Default" derived from (2.1.3.2) is not a default probability because "it does not correspond to the true probability of default in large samples. In contrast, the default probabilities calculated by KMV are indeed default probabilities because they are calculated using the empirical distribution of defaults. For that reason, we do not call our measure default probability, but rather default likelihood indicators (*DLI*)". Following Vassalou and Xing (2004), we call the measure of default probability in (2.1.3.2) as *DLI* in this paper.

Given that the value of the firm's assets follows the stochastic process as described in (2.1.1.1) and the initial value is A', the market value of the firm's assets at time *t* is

$$lnA_t = lnA' + \left(\mu - \frac{\sigma_A^2}{2}\right)t + \sigma_A \cdot \sqrt{t} \cdot \varepsilon \tag{2.1.3.3}$$

where ε is the random component of the firm's return.

According to (2.1.4.1) and (2.1.4.2), the *DLI* can be written as

$$DLI_t = Pr\left[lnA' + \left(\mu - \frac{\sigma_A^2}{2}\right)t + \sigma_A \cdot \sqrt{t} \cdot \varepsilon \leq lnF\right] \tag{2.1.3.4}$$

and after rearranging

$$DLI_t = Pr\left[-\frac{ln\frac{V_A}{F} + \left(\mu - \frac{\sigma_A^2}{2}\right)t}{\sigma_A \cdot \sqrt{t}} \geq \varepsilon\right] \tag{2.1.3.5}$$

Under the assumption that ε is normally distributed, ε~N(0,1), (2.1.3.5) can be defined as

$$DLI_t = N\left[-\frac{ln\frac{A\prime}{F}+\left(\mu-\frac{\sigma_A^2}{2}\right)t}{\sigma_A\cdot\sqrt{t}}\right] \quad (2.1.3.6)$$

The Distance to Default (*DD*) is given by

$$DD = \frac{ln\frac{A\prime}{F}+\left(\mu-\frac{\sigma_A^2}{2}\right)t}{\sigma_A\cdot\sqrt{t}} \quad (2.1.3.7)$$

Statistically, the result of the calculation from (2.1.3.7) can be interpreted as by how many standard deviations move in the assets' value will the firm default (the default is assumed to happen when the value of the firm's assets is lower than that of the debt).

2.2 The accounting models and bond market based models

2.2.1 The accounting models

The accounting models use accounting data to predict the probability that a loan applicant or existing borrower will default or be delinquent (Mester, 1997). This branch of default risk models can be divided into two broad categories by the number of variables used within the model, namely univariate accounting model and the multivariate accounting model (Altman & Saunders, 1998). As it is argued by Altman & Saunders (1998) that the univariate accounting models compare various key accounting ratios of creditors with the industry norms whereas the multivariate accounting models combine and weight a bunch of key accounting variables to produce either a credit risk score[14] (obtained in the multiple discriminant analysis model) or a probability[15] (obtained in the linear probability model, the logit model or the probit model). In most accounting models, lower score indicates higher risk. For example, lower score indicates higher risk in the Z-score model (Altman E. I., 1968).

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[14] See Z-score model (Altman, 1968), ZATA-score model (Altman et al., 1977), and etc..

[15] See O-score model (Ohlson, 1980), and etc..

Table 2.2.1.1 International survey of accounting models

STUDIES CITED	EXPLANATORY VARIABLES
United States	
Altman (1968)	EBIT/assets; retained earnings/assets; working capital/assets; sales/assets; market value (MV) equity/book value of debt.
Japan	
Ko (1982)	EBIT/sales; working capital/debt; inventory turnover 2 years prior/inventory turnover 3 years prior; MV equity/debt; standard error of net income (4 years).
Takahashi, et. al. （1979）	Net worth/fixed assets; current liabilities/assets; voluntary reserves plus unappropriated surplus/assets; interest expense/sales; earned surplus; increase in residual value/sales; ordinary profit/assets; sales - variable costs.
Switzerland	
Weibel (1973)	Liquidity (near monetary resource asset - current liabilities)/operating expenses prior to depreciation; inventory turnover;debt/assets.
Germany	
Baetge, Huss and Niehaus (1988)	Net worth/(total assets － quick assets － property & plant); (operating income + ordinary depreciation + addition to pension reserves)/assets; (cash income - expenses)/short term liabilities.
Von Stein & Ziegler (1984)	Capital borrowed/total capital; short-term borrowed capital/output; accounts payable for purchases & deliveries/material costs; (bill of exchange liabilities + accounts payable)/output; (current assets - short-term borrowed capital)/output; equity/(total assets - liquid assets - real estate); equity/(tangible property - real estate); short-term borrowed capital/current assets; (working expenditure - depreciation on tangible property)/(liquid assets + accounts receivable - short-term borrowed capital); operational result/capital; (operational result + depreciation)/net turnover; (operational result + depreciation)/short-term borrowed capital; (operational result + depreciation)/total capital borrowed.
England	
Marais (1979), Earl & Marais （1982）	Current assets/gross total assets; 1/gross total assets; cash flow/current liabilities; (funds generated from operations - net change in working capital)/debt.
Canada	
Altman and Lavallee (1981)	Current assets/current liabilities; net after-tax profits/debt; rate of growth of equity － rate of asset growth; debt/assets; sales/assets.
The Netherlands	
Bilderbeek (1979)	Retained earnings/assets; accounts payable/sales; added value/ assets; sales/assets; net profit/equity.
van Frederikslust (1978)	Liquidity ratio (change in short term debt over time); profitability ratio (rate of return on equity).

Table 2.2.1.1 (continued)	
STUDIES CITED	EXPLANATORY VARIABLES
Spain	
Fernandez (1988)	Return on investment; cash flow/current liabilities; quick ratio/ industry value; before tax earnings/sales; cash flow/sales; (permanent funds/net fixed assets)/industry value.
Italy	
Altman, Marco, and Varetto (1994)	Ability to bear cost of debt; liquidity; ability to bear financial debt; profitability; assets/liabilities; profit accumulation; trade indebtedness; efficiency.
Australia	
Izan (1984)	EBIT/interest; MV equity/liabilities; EBIT/assets; funded debt/ shareholder funds; current assets/current liabilities.
Greece	
Gloubos & Grammatikos (1988)	Gross income/current liabilities; debt/assets; net working capital/assets; gross income/assets; current assets/current liabilities.
Brazil	
Altman, Baidya, & Ribeiro-Dias (1979)	Retained earnings/assets; EBIT/assets; sales/assets; MV equity/ book value of liabilities.
India	
Bhatia (1988)	Cash flow/debt; current ratio; profit after tax/net worth; interest/ output; sales/assets; stock of finished goods/sales; working capital management ratio.
Korea	
Altman, Kim & Eom (1995)	Log(assets); log(sales/assets); retained earnings/assets; MV of equity/liabilities.
Singapore	
Ta and Seah (1981)	Operating profit/liabilities; current assets/current liabilities;EAIT/paid-up capital; sales/working capital; (current assets - stocks - current liabilities)/EBIT; total shareholders ’ fund/liabilities; ordinary shareholders’ fund/capital used.
Finland	
Suominen (1988)	Profitability: (quick flow – direct taxes)/assets; Liquidity: (quick assets/total assets); liabilities/assets.
Uruguay	
Pascale (1988)	Sales/debt; net earnings/assets; long term debt/total debt.
Turkey	
Unal (1988)	EBIT/assets; quick assets/current debt; net working capital/sales; quick assets/inventory; debt/assets; long term debt/assets.

Whenever possible, the explanatory variables are listed in order of statistical importance (e.g., the size of the coefficient term) from highest to lowest. Source: (Allen, DeLong, & Saunders, 2003).

Accounting models have been frequently applied in both academic researches and practice[16] on their establishments. The previous studies not only apply different methodological approaches (e.g. the multiple discriminant analysis model, the linear probability model, the logit model or the probit model), but also utilize use different kind of accounting variables. Table 2.2.1.1 from Allen, DeLong, & Saunders (2003) gives a brief overview of previous empirical studies on accounting models.

On the one hand, the abundant studies on accounting models reveal that such models are predominately limited to the quality and availability of the balance sheet data, and the assumption of linearity. In addition it is argued that the volatility of the firm's assets[17] contains important information about the firm's default risk, however accounting models do not take into account the volatility of the firm's assets in estimating its default risk as equity market based models do. Moreover accounting models are blamed to use the accounting data from historical financial statement which is inherently backward looking while the equity market based models apply the market value of the firm's equity, which reflects the expectation of the firm's future performance (Vassalou & Xing, 2004). All these showed above make equity market based models superior default forecasting models compared with accounting models.

On the other hand, accounting models are relatively inexpensive to implement. And most studies found that financial ratios measuring profitability, leverage and liquidity had the most statistical power in differentiating defaulted from non-defaulted firms.

Since information contained in these financial ratios is by no means included in Merton-KMV model, some previous studies argue that we can combine financial ratios measuring profitability, leverage and liquidity with the Merton-KMV model to increase the predictive power of the Merton-KMV model. For example, Keenan &

[16] For example, a survey conducted by the Federal Reserve board shows that "97 percent of the responding banks that use credit-scoring in their credit card lending operations use it for approving card applications" (Federal Reserve Board, 1996).

[17] For example, Campbell and Taksler (2003) reveal that the volatility of the firm and credit ratings can explain the cross-sectional variation in corporate bond yields as well as credit rating (Vassalou & Xing, 2004).

Sobehart (1999) found that by adding information such as profitability, we can significantly improve upon a model that uses a stricter interpretation of the Merton framework (Keenan & Sobehart, 1999). Thus in this paper we will also add financial ratios measuring profitability, leverage and liquidity, in conjunction with the Merton-KMV model to see if we can improve the predictive power of the Merton-KMV model.

2.2.2 The bond market based models

As it comes to the bond market based models, one may utilize corporate bond spread or bond rating to calculate firms' default risk.

A firm defaults when it fails to meet the obligation of paying its debt. This default risk induces creditors to ask for a spread over the risk-free rate. Thus the excess return from the corporate bonds relative to the risk-free rate of interest would reveal the default risk of the firm. However a number of empirical studies[18] have shown that default risk only takes up a small percentage of the spread and extracting the former one from the latter is a non-trivial spread-decomposition work (Tudela & Young, 2005).

Rating agencies group borrowers into several rating grades. Default probabilities are assigned to a grade by calculating the observed default rate of all borrowers within this grade in each year and averaging these figures over a historical horizon. Patel & Vlamis (2007) provide a table which matches of different levels of theoretical DLI and risk rating according to Standard and Poor's rating services (see table 2.2.2.1).

[18] See Elton et al. (2001), Huang and Huang (2002), Colllin-Dufresne et al. (2001), and etc..

Table 2.2.2.1 DLI and bond rating symbols

DLI (in basis points)	Corresponding S&P rating	Interpretation
0-2	AAA	Highest quality: Extremely strong capacity. Excellent business credit, superior asset quality.
2-4	≥AA	Highest quality: Extremely strong capacity. Excellent business credit, superior asset quality, excellent debt capacity and coverage; excellent management with depth. Company is a market leader and has access to capital markets.
4-10	AA-A	High quality, very strong capacity. Good business credit, very good asset quality and liquidity, strong debt capacity and coverage, very good management in all positions. Company is highly regarded in industry and has a strong market share.
10-19	A-BBB^{+}	Strong payment capacity. Average business credit, within normal credit standards: satisfactory asset quality and liquidity, good debt capacity and coverage, good management in all positions. Company is of average size and position within the industry.
19-40	BBB^{+}-BBB^{-}	Adequate payment capacity. Acceptable business credit, but with more than average risk, acceptable asset quality, little excess liquidity, modest debt capacity. May be highly leveraged. Requires above-average levels of supervision and attention from lender. Company is not strong enough to sustain major setbacks.
40-72	BBB^{-}-BB	Likely to fulfill obligations.
72-101	BB-BB^{-}	Acceptable business credit but with considerable risk, acceptable asset quality, smaller and/or less diverse asset base, very little liquidity, limited debt capacity. Covenants structured to ensure adequate protection. May be highly or fully leveraged. May be below-average size or a lower-tier competitor. Requires significant supervision and attention from lender. Company is not strong enough to sustain major setbacks.
101-143	BB^{-}-B^{+}	Ongoing uncertainty
143-202	B^{+}-B	Watch list credit: generally acceptable asset quality, somewhat strained liquidity, fully leveraged. Some management weakness, requires continual supervision and attention from lender.

Table 2.2.2.1	(continued)	
DLI (in basis points)	**Corresponding S&P rating**	**Interpretation**
202-345	B- B^-	High-risk obligations.
345-1500	CCC^+-CC	Current vulnerability to default. Unacceptable business credit, normal repayment in jeopardy. Although no loss of principal or interest is envisioned, a positive and well-defined weakness jeoparizes collection of debt. The asset is inadequately protected by the current sound net worth and paying capacity of the obligor or pledged collateral.
1500-2000	CC-D	In bankruptcy or default. Expected total loss. An uncollectable asset or one of such little value that it does not warrant classification as an active asset. Such an asset may, however, have recovery or salvage value, but not to the point where a write-off should be deferred, even though a partial recovery may occur in the future.

Source: (Patel & Vlamis , 2006)..

However it is worth noticing here that the philosophies are different for these two types of default risk forecasting methods: Through the Cycle (bond rating) versus Point in Time Ratings (Merton-KMV). Merton-KMV model reflects a borrower's situation and the most likely future condition over an exactly pre-specified horizon (e.g. one year) while bond ratings focus on the long term over one or more business cycles. Thus *DLI* from the Merton-KMV changes as soon as the borrowers' condition changes while an assigned bond rating is nearly constant overtime. In other words, *DLI* from the Merton-KMV is more volatile than bond rating.

In addition, when the movement of the bond from one grade to another is used to estimate the firm's default risk, it implicitly but mistakenly assumed that bonds with similar grade share the same default risk which is just the average of the historical default risk (Vassalou & Xing, 2004).

All the reasons listed above show that the bond market based models are not better in predicting firm's default risk than equity market based Merton-KMV model. Thus the Merton-KMV is the method followed in this paper.

2.3 Recent empirical studies on Merton-KMV model

Over the recent years, a number of researches have made their efforts to examine the contribution of the Merton-KMV model. Papers that examine the predictive power of the Merton-KMV model include Hillegeist et al. (2004), Tudela & Young (2005), Du & Suo (2007), Patel & Vlamis (2007), Duffie et al. (2007), Bharath & Shumway (2008), and etc.. Although most papers demonstrate that the Merton-KMV is a useful method in predicting default risk, researchers have not reached a consensus as to whether this model can be improved by adding other variables. Among all the empirical studies, Tudela & Young (2005), Patel & Vlamis (2007) and Bharath & Shumway (2008) provide a good framework and some helpful thoughts for this paper.

Tudela & Young (2005) examine the reliability and efficiency of the Merton-KMV model in predicting the default risk of individual quoted UK companies. Tudela & Young (2005) collect 7,459 financial statements from 1990 to 2011, 65 of which correspond to default, and calculate the *1-year "Default Likelihood Indicators" (DLI) annual average* and the *2-year DLI annual average*[19]. By comparing the calculation results with the actual situation, Tudela & Young (2005) demonstrate that both of the *1-year DLI annual average* and the *2-year DLI annual average* can be used to discriminate between the healthy firms and the defaulted firms. However Tudela & Young (2005) also reveal that the predicting power of the Merton-KMV model can be improved by incorporating company account information.

Patel and Vlamis (2007) argue that under the "risk neutral" *DLI* measurement, the expected return on the firm's asset, is the riskless interest rate *r*. Based on the "risk neutral" assumption, Patel and Vlamis (2007) examine the *DD* and the "risk neutral" *DLI* for a sample of 112 real estate companies listed in UK during the period from 1980 to 2001. The "risk neutral" *DLI* credits are then transformed to risk rating

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[19] The *1-year DLI annual average* is the simple average of the 1-year ahead *DLIs* in each month of the preceding calendar year while the *2-year DLI annual average* is the simple average of the 2-year ahead *DLIs*, - from the 12th month before the default to the 24th before the default month.

according to *Standard and Poor's* rating service, with which Patel and Vlamis (2007) are able to assess the creditworthiness of an obligor with respect to a specific obligation. The final results reveal that the Merton-KMV model correctly predicts the default when it did occur. However 12 out of 112 companies are mistakenly predicted to default when they are in fact healthy companies. Patel and Vlamis (2007) finally argue that their results support the theoretical idea of the Merton-KMV model that the two driving forces are high leverage and high asset volatility.

Bharath and Shumway (2008) examine the accuracy and contribution of the Merton-KMV model by testing three hypotheses: 1) the *DLI* derived is a sufficient statistic for forecasting bankruptcy; 2) the functional form used to calculate *DLI* given above is an important construct for predicting default; 3) the solution of the Merton-KMV model is salient for predicting default. To test these hypotheses, Bharath and Shumway (2008) compare *DLI* from (2.1.4.5) with several other default forecasting variables and the following four alternatives: a. naïve *DLI* that derived from naïve alternative, which does not require iteratively solving (2.1.1.3) and (2.1.1.6) but mimics the function form (2.1.4.5); b. "risk neutral" *DLI*; c. *PD* from directly solving (2.1.1.3) and (2.1.1.6); d. *DLI* from using option-implied volatility of firm equity. By examine all firms in the section of the Compustat Industry file, among which 1449 firms default according to the Altman default database and the list of defaults published by Moody's during the period from 1980 to 2003, Bharath and Shumway (2008) reveal that the Merton-KMV model is reliable but not an efficient method in predicting the default risk.

3. Chinese institutional background

As it is reported by Pedone & Liu (2010) that compared with developed market, Chinese market has witnessed a relative small number of bankruptcy filings, for example, 8,162 in March 2009 alone for America versus 2,900[20] in 2009 for China (Pedone & Liu, 2010). The relative rarity of defaults in China may partly contribute to the special institutional environment in China. As these institutional factors will give us different definition of default compared with that used in American papers and thus influence our empirical results, in this section, brief introduction of Chinese institutional background will be given before we start our empirical research.

3.1 Security market

3.1.1 Historical background of firms

The security markets in China are quite different from developed market due to the historical background of firms. China maintained a centrally planned, or command, economy since its establishment in 1949 and until the end of 1978. Under the centrally planned economy, a majority of the firms were owned by the state, meaning that a number of listed firms are originally state-owned enterprises (hereafter SOEs) Although China has experienced the transition from the centrally planned economy to the market economy since 1978 and witnessed a great number of the SOEs being changed into corporate entities, China Corporate Governance Survey (2007) shows that the state still holds a majority share of the listed companies and SOEs constitute close to 90 percent of the total listed companies in China in 2005 (CFA, 2007). Moreover shares owned by the state are not allowed to be traded in the stock exchange. In other words, stocks in Chinese market are categorized into tradable and

[20] Note that this data indicates the number of bankruptcy cases adopted by the courts in mainland China in 2009. And the definition of “bankruptcy” here is different to what is used in our empirical study later. In addition, the bankruptcy cases of non-listed companies are included here while in our empirical study showed later, only listed firms will be studied.

non-tradable share. Intuitively it is easier to manipulate the price for stocks with high non-tradable shares (Altman, Zhang, & Yen, 2007). Since one of the important inputs for the Merton-KMV model is the observable stock price, the "distorted" stock price may make the "Default Likelihood Indicators" (*DLI*) biased. More specifically *DLI* calculated from the Merton-KMV model may be lower than "actual" *DLI* since companies tend to cover the "bad" news.

On April 29, 2005, the China Securities Regulatory Commission (CSRC) starts the Share Merger Reforms to convert non-tradable shares into tradable shares. The reform accelerates the process of the privatization, i.e. shifting the balance of share ownership from government ownership to public ownership by minority shareholders, especially among institutional investors, meaning that the shareholders of Chinese listed companies are more diversified after 2005. The diversification of the shareholders lowers the possibility to manipulate the price for stocks.

3.1.2 Secondary Market

In mainland China, Shanghai Stock Exchange and Shenzhen Stock Exchange, which are two membership institutions governed directly by the China Securities Regulatory Commission (CSRC), provide places and facilities for centralized transactions.

Shanghai Stock Exchange, which was first established in 1929 but closed in 1949 during the Communist Revolution, was reopened in 1990. Opened in the same year, Shenzhen Stock Exchange is committed to "developing China's multi-tier capital market system, serving national economic development and transformation and supporting the national strategy of independent innovation" (Shenzhen Stock Exchange , 2011).

China's secondary market is divided into three segments, respectively Main Board, Small and Medium Enterprises Board (hereafter SME Board) and ChiNext (also known as the "third board"). Main Board, just as the name implies, is the main place that stocks are listed and traded. Stocks listed in Main Board usually belong to mature companies with relative large firm size and high level of profitability. SME Board was inaugurated on 27 May for small- and mid-caps with pronounced core business, high growth potential and intensive technological contents. Delisted distressed firms from Main Board and SME Board are moved to ChiNext and traded once a week rather than go bankruptcy directly. This is considered to protect investors from suffering giant losses without creating further social problem by keeping the problematic firms in regular board. The multi-tier capital market system may also contribute to the relative rarity of bankruptcy filings in China.

3.2 Bankruptcy law and practice

China has a relative short bankruptcy practice history compared with that of the developed market. There was no bankruptcy system in practice for more than thirty years after 1949, when the People's Republic of China is announced to be established. The first bankruptcy law for SOEs was enacted in 1986. However the judicial system on bankruptcy is obsolete and law enforcement is weak. As it is described by Fan et al. (2008) that "Judges and attorneys alike often find themselves lack the specific clauses to resort to in the law or law enforcement to carry out what the court rules. As a result, the court system has been very conservative with bankruptcy-related petitions so as not to contradict the interpretation of the law. The court normally requires distressed firms to first obtain consent to their bankruptcy decisions from the local government and to propose a satisfactory plan to place its existing employees, before even considering handling the cases."

The new Enterprise Bankruptcy Law, which applies to all kind of enterprises, became effective since June 2007. Enterprise Bankruptcy Law gives an overall guild for bankruptcy practice in China but lacks details present in other insolvency statutes around the world (Pedone & Liu, 2010). The Supreme People's Court, the highest court of the PRC, facilitates Enterprise Bankruptcy Law with the judicial interpretations. Although introducing advanced market-orientated bankruptcy mechanics, Enterprise Bankruptcy Law has not file a single listed firm for bankruptcy yet. There may be two important reasons for the lack of use of Enterprise Bankruptcy Law after it was implemented. One reason is that local government has much influence in deciding whether distressed firms should go through bankruptcy process. And usually the government tends to protect these firms by encouraging reconstruct rather that bankruptcy because: 1) the number of listed corporations under the governance of a local government is generally connected with the local economic prosperity and the officials' performance (Li & Wang, 2009); 2) the top priority of such firms may be increasing the employment rather than making profit (Altman, Zhang, & Yen, 2007). The other reason is that China still generally lacks specialized bankruptcy courts, judges, and professionals familiar with bankruptcy proceedings (Pedone & Liu, 2010).

4. Methodology

4.1 Assumptions

The Merton-KMV is based on some strict assumption. Before applying this model to calculate the "Default Likelihood Indicators" (*DLI*) for Chinese listed companies, we have to identify some of the important assumptions, which are listed as follows: 1) Chinese financial market is perfect (e.g. no arbitrage opportunity, no transaction cost, etc.); 2) firms' asset value follows geometric Brownian motion.

4.2 Sample selection

Our empirical work begins with the definition of default. Previous studies in America usually define defaults as bankruptcy filings under either Chapter 7 or Chapter 11 of the bankruptcy code. However, this definition is not suitable for this paper as it is showed in section 3 that by far China has no bankruptcy filings for listed firms due to the following reasons: 1) instead of directly going bankruptcy, the problematic firms are allowed to move from Main Board or SME Board to the third board; 2) the bankruptcy law is still in its initial phase and China lacks specialized bankruptcy courts, judges, and professionals familiar with bankruptcy proceedings; 3) Chinese government tends to protect listed firms from going bankruptcy. Thus default in this paper is defined more broadly as a firm being delisted from Shanghai or Shenzhen Stock Exchanges for financial reasons [21], an event that sometimes precedes bankruptcy or formal default (Campbell, Hilscher, & Szilagyi, 2008). The time of default is the year of being delisted. Both the name of the delisted companies and the time of being delisted can be obtained from the website of Shanghai Stock Exchange (http://www.sse.com.cn) and Shenzhen Stock Exchange (http://www.szse.cn).

[21] "Typical financial reasons to delist a stock include failure to maintain market capitalization or stock price. Nonfinancial reasons to delist a stock include M&A." (Campbell, Hilscher, & Szilagyi, 2008)

The surviving firms are the full list of the companies that alive in 2010 and issue A-shares[22] in Shanghai and Shenzhen Stock Exchanges. The surviving sample is then screened according to the following criteria:

1. Exclude the financial companies, the capital structure of which is distinguished from that of common ones.
2. Exclude the “PT” companies and “ST” companies since their financial status are abnormal.
3. Exclude the companies with incomplete data.

The study period is from 2000 through 2010.

4.3 Testing procedure

4.3.1 Computing “Default Likelihood Indicators” (*DLI*)

Following Bharath & Shumway (2008), we start by estimating the “Default Likelihood Indicators” (*DLI*) for our whole sample using the Merton-KMV model showed in section 2. There are five important variables, respectively the market value of firm’s equity E_t, the volatility of the stock returns σ_E, the riskless interest rate *r*, the face value of the debt, *F*, and the time period *T*.

1. The market value of firm’s equity E_t is calculated as the product of historical annual share price and the number of the share outstanding at the end of the year.
2. The volatility of the stock returns σ_E is annualized standard deviation of the monthly equity return from the past 24 months.
3. The face value of the firm’s debt, *F*, can be calculated from (2.1.3.1) mentioned above. The annual data for the book value of the short-term debt

[22] A-shares are specialized shares of the Renminbi currency that are purchased and traded on the Shanghai and Shenzhen stock exchanges. This is contrast to B-shares which are owned by foreigners who cannot purchase A-shares due to Chinese government restrictions and they are measured by foreign currency.

and the long-term debt are used in this paper.

4. As for the riskless interest rate *r*, we use the annual deposit interest rate, which can be obtained from the website of the *People's Bank of China*. These annual deposit interest rates are then translated into annually continuous interest rate.
5. The forecasting window, *T*, is set to be 1 year here.

We use annual market data and annual accounting data here. The firm-level market data and accounting data mentioned above can be obtained from *iFind*[23].

4.3.2 Examine the significance and efficiency of the Merton-KMV model

After calculating the "Default Likelihood Indicators" (*DLI*) for our whole sample, we will examine the following three hypotheses.

First, we will test whether the "Default Likelihood Indicators" (*DLI*) calculated from the Merton-KMV model is a significant statistic to predict default in Chinese market.

Hypothesis 1

H_0: *DLI* is a significant statistic to predict default in Chinese market.

H_1: *DLI* is not a significant statistic to predict default in Chinese market.

Second, we will examine whether the "Default Likelihood Indicators" (*DLI*) calculated from the Merton-KMV model is a sufficient statistic to predict default in Chinese market. As it is argued by Bharath & Shumway (2008) that if the "Default Likelihood Indicators" (*DLI*) is a sufficient statistic to predict default, it should be impossible to improve on the model's implied probability for predicting. In other words, all the information needed to predict default is included in the "Default Likelihood Indicators" (*DLI*).

[23] iFind is a Chinese database that provides financial and economic data of Chinese market.

Hypothesis 2

H_0: *DLI* is a sufficient statistic to predict default in Chinese market.

H_1: *DLI* is not a sufficient statistic to predict default in Chinese market.

Third, we will test whether the functional form used by the Merton-KMV model adds value for predicting default.

Hypothesis 3

H_0: The functional form used by the Merton-KMV model adds value for predicting default.

H_1: The functional form used by the Merton-KMV model does not add value for predicting defaults.

Different from Bharath & Shumway (2008) which employs a Cox proportional hazard model to test the three hypotheses, we construct a much simpler econometric model in this paper to assess the performance of the Merton-KMV model. First we need an indicator of default. Then we will regress indicator of default on the "Default Likelihood Indicators" (*DLI*) calculated from the Merton-KMV model to see if the it is statistically significant.

It has been mentioned above that the defaulted firm in this paper is defined as a firm which is delisted from Shanghai or Shenzhen Stock Exchanges for financial reasons, thus the indicator of default equals 1 at time *t-1*[24] if it is delisted from Shanghai or Shenzhen stock exchanges for financial reasons at time *t*, and zero otherwise.

We then simply regress the binary indicator of the default on the DLI_{t-1} calculated from the Merton-KMV model. Usually we use a linear probability model (LPM hereafter) to do the binary regression because it is simple to estimate and use. However it is worth noticing that the dependent variable is a dummy variable, which takes a number either of unity or zero. When using a LPM, the fitted probabilities can be less than zero or greater than one. Besides, the partial effect of any explanatory

24 The predicting window is set to be 1 year in this paper.

variable estimated by LPM is constant (Wooldridge, 2009). These limitations of the LPM can be overcome by using more sophisticated binary response models, e.g. logit model. Thus we construct a dynamic logit model here as follows:

$$P_{t-1}\left(Y_{i,t}=1\right)=\frac{exp\left(\alpha+\beta_0 DLI_{i,t-1}+\varepsilon_{i,t-1}\right)}{1+exp\left(\alpha+\beta_0 DLI_{i,t-1}++\varepsilon_{i,t-1}\right)} \quad (4.3.2.1)$$

where $Y_{i,t}$ is a binary indicator of default for firm *i* in any year *t*, which equals one if firm *i* is delisted for financial reasons in year *t*, and zero otherwise, in particular, the indicator is zero if the firm disappears from the data set for some reason other than bankruptcy such as acquisition, $DLI_{i,t-1}$is the estimation from the previous year, and $\varepsilon_{i,t-1}$is the error term.

Model 1 can be used to test hypothesis 1, if the result shows that the coefficient of $DLI_{i,t-1}$ is statistically significant, we can accept the null hypothesis and conclude that the "Default Likelihood Indicators" (*DLI*) calculated from the Merton-KMV model is a significant statistic to predict default in Chinese market.

To test hypothesis 2, we construct a dynamic logit model as follows:

$$P_{t-1}(Y_{i,t}=1)=\frac{\exp\left(\alpha+\beta_0 DLI_{i,t-1}+\beta_1 NINA_{i,t-1}+\beta_2 TLTA_{i,t-1}+\beta_3 LASTL_{i,t-1}+\varepsilon_{i,t-1}\right)}{1+exp\left(\alpha+\beta_0 DLI_{i,t-1}+\beta_1 NINA_{i,t-1}+\beta_2 TLTA_{i,t-1}+\beta_3 LASTL_{i,t-1}+\varepsilon_{i,t-1}\right)} \quad (4.3.2.2)$$

where $NINA_{i,t-1}$ is the ratio of net income to total assets for firm *i* in year *t-1*, $TLTA_{i,t-1}$ is the total liabilities relative to total assets for firm *i* in year *t-1* and $LASTL_{i,t-1}$ is the ratio of a company's liquid assets to its short-term liabilities for firm *i* in year *t-1*.

As we discussed in section 2.2.2 that most studies found financial ratios measuring profitability, leverage and liquidity had the most statistical power in differentiating defaulted from non-defaulted firms. Since information contained in these financial ratios is by no means included in Merton-KMV model, some previous studies argue that we can combine these financial ratios with Merton-KMV model to increase the predictive power of the Merton-KMV model. For example, Keenan & Sobehart (1999) found that by adding information such as profitability, we can significantly improve upon a model that uses a stricter interpretation of the Merton framework (Keenan & Sobehart, 1999). Thus in this paper we will also add financial ratios measuring profitability, leverage and liquidity, in conjunction with Merton-KMV model to see if we can improve the predictive power of the Merton-KMV model. Again annual data is used here. If the results show that $DLI_{i,t-1}$is the only variable that is statistically significant, we can accept the null hypothesis and conclude that DLI calculated from the Merton-KMV model is a sufficient statistic to predict default in Chinese market. Before doing this test, we have to examine the significance of the financial ratios in predicting default. We cannot improve the predictive power of the Merton-KMV model by adding financial ratios that contains no useful information at all. We will test the information content of the accounting data with the following model:

$$P_{t-1}\left(Y_{i,t} = 1\right) = \frac{\exp\left(\alpha+\beta_1 NINA_{i,t-1}+\beta_2 TLTA_{i,t-1}+\beta_3 LASTL_{i,t-1}+\varepsilon_{i,t-1}\right)}{1+exp\left(\alpha+\beta_1 NINA_{i,t-1}+\beta_2 TLTA_{i,t-1}+\beta_3 LASTL_{i,t-1}+\varepsilon_{i,t-1}\right)} \qquad (4.3.2.3)$$

We will only use financial ratios that are statistically significant from the regression (4.3.2.3) to test hypothesis 2 with model (4.3.2.2).

To test the third hypothesis, we can include the "Default Likelihood Indicators" (*DLI*) and the inputs that are needed to calculate *DLI* as independent variables. If the result shows that $DLI_{i,t-1}$ remains statistically significant, we can accept the null hypothesis and demonstrate that the functional form used by Merton-KMV model does add value for predicting default. Otherwise we can conclude that all the useful information in predicting defaults is included in the inputs of the Merton-KMV model and the functional form used by Merton-KMV model does not add value for predicting default. The dynamic logit model that is used to test hypothesis 3 is constructed as follows:

$$P_{t-1}(Y_{i,t} = 1) = \frac{\exp\left(\alpha+\beta_0 DLI_{i,t-1}+\beta_4 lnE_{i,t-1}+\beta_5 lnF_{i,t-1}+\beta_6 1/\sigma_{E_{i,t-1}}+\varepsilon_{i,t-1}\right)}{1+exp\left(\alpha+\beta_0 DLI_{i,t-1}+\beta_4 lnE_{i,t-1}+\beta_5 lnF_{i,t-1}+\beta_6 1/\sigma_{E_{i,t-1}}+\varepsilon_{i,t-1}\right)} \qquad (4.2.3.4)$$

where $lnE_{i,t-1}$ is the log of the firm's equity value, $lnF_{i,t-1}$ is the log of the firm's debt and $1/\sigma_{E_{i,t-1}}$ is the inverse of the firm's equity volatility. All of the three variables are important inputs for the Merton-KMV model.

5. Data description

Table 5.1 summarizes the annual number of defaults as well as the number of total listed companies during our sample period in China. The first column shows the total number of listed firms in Chinese market, which is computed by summing the listed firms from Shanghai Stock Exchange and Shenzhen Stock Exchange for every year. The second column indicates the number of defaults each year. And the third column is the corresponding percentage of listed firms that are defaulted during the sample period.

Table 5.1 Distributions of the Number of Defaulted Firms by Year

Year	No. of Stocks	No. of Defaults	(%)
2001	1160	3	0.26%
2002	1224	7	0.57%
2003	1287	4	0.31%
2004	1377	8	0.58%
2005	1381	11	0.80%
2006	1434	6	0.42%
2007	1550	6	0.39%
2008	1625	0	0.00%
2009	1718	0	0.00%
2010	2165	0	0.00%
Total number of defaults: 45			

Table 5.1 summarizes the full sample of defaults by time in Chinese market during the period from 2001 to 2010; in total there are 68 firm delisted from the Shanghai Stock Exchange or Shenzhen Stock Exchange, however, among all of the delisted firms 23 firms are delisted for the reason of M&A and only 45 firms meet our definition of default, i.e. being delisted for financial distress. The total number of listed firms per year indicates all the quoted firms which can be obtained from the website of Shanghai Stock Exchange and Shenzhen Stock Exchange, however not all the firms are included in our sample due to the data availability.

It can be easily seen that although we define default more broadly than American academics, the number of defaulted listed firms is still incredibly small.

The defaults reach its peak in 2005. This may partly contributed to the *Share Merger Reforms* in Chinese stock market during 2005 argued in section 3. Historically a majority of Chinese listed companies are owned by the state. And for such state-owned listed companies, not all the shares of stock are tradable in the market. Intuitively it is easier to manipulate the price for stocks with high non-tradable shares. By doing so, companies with bad performance avoid being "punished" by the market. In other words, companies that are qualified for default continue to live by manipulating the price for stocks. On April 29, 2005, the China Securities Regulatory Commission (CSRC) announced a reform plan to abolish the split-share structure. According to the circular, all listed companies have to choose a suitable time to merge their tradable and non-tradable shares. Listed companies which complete the merger would be given priority to raise new capital; and all shares in future initial public offerings will be tradable. The *Share Merger Reforms* accelerates the default of the problematic firms which used to cover the "bad news".

It is also worth noticing here that the number of defaults does not increase in 2007, when the new Enterprise Bankruptcy Law became effective. In addition, there are no defaults during the worldwide financial crisis.

Table 5.2 summarizes the properties of some main inputs that are needed to calculate the *DLI* and some other potential explanatory variables that are required during the testing procedure. Our data set covers most of the companies listed in Chinese market during 2000 and 2010 with complete data availabilities. In total there are 7257 observations in our sample. Among all the observations, 39 firms[25] belong to defaulted group. Panel A in Table 5.2 describes variables in our whole sample, Panel B reveal a subsample of 7218 surviving observations and Panel C is the defaulted group.

Column (1) to (2) present descriptive statistics of the three main variables needed to calculate the *DLI*, namely the market value of the firm, *E*, the face value of the firm's debt, *F*, and the annualized volatility of the firm's stock price. It is obvious showed in

[25] We report in table 5.1 that there are 45 firms meet our definition of default during our study period, however due to the data availability, only 39 of them are include in our sample.

table 5.2 that the mean value of the market capitalization for the surviving group is 8501.1 million RMB, whereas that for the default group is 6733 million RMB. Besides, the mean value of the debt for default group is also smaller than that for the surviving group. In other words, compared with the surviving firms, defaulted firms have smaller firm size. It can also be seen that the stock value volatility is higher within default sample. This gives us the fist impression that the defaulted sample has higher risk than the surviving sample.

Column (4), column (5) and column (6) respectively present descriptive statistics for three financial ratios. It is interesting that the mean value of *NITA* is negative for defaulted firms but positive for surviving firms, revealing that defaulted firms in fact make losses in average while survival firms are profitable. This discovery matches up to our common sense. Column (5) tells us that the mean value of the leverage is much higher for defaulted sample than that for surviving sample. This is not surprising since defaulted firms are those that are failed to meet their debt obligations, higher level of leverage means heavier burden. Last column reveals that generally surviving firms have much higher liquidity than defaulted firms, which is also what we expected.

Table 5.2 Summary Statistics for Some Important Variables

Variables	(1) E	(2) F	(3) σ_E	(4) NITA	(5) TLTA	(6) LASTL
			Panel A. Whole Data Set			
Mean	84.590	13.794	0.466	0.050	0.576	1.281
Std. Dev.	529.812	46.754	0.177	0.106	0.573	0.809
Min	0.764	0.025	0.117	-2.764	0.054	0.002
Max	25293.500	1139.640	1.919	2.092	23.799	20.106
Observations: 7257						
			Panel B. Surviving Group			
Mean	85.011	13.850	0.466	0.053	0.558	1.286
Std. Dev.	531.211	46.873	0.178	0.086	0.346	0.808
Min	1.487	0.025	0.117	-1.587	0.054	0.028
Max	25293.500	1139.640	1.919	2.092	16.329	20.106
Observations: 7218						
			Panel C Defaulted Group			
Mean	6.7330	3.4711	0.5010	-0.5140	3.9328	0.3514
Std. Dev.	5.1611	2.7143	0.0898	0.6535	5.3272	0.3586
Min	0.7638	0.1162	0.3465	-2.7642	0.3417	0.0023
Max	23.1494	10.4769	0.7090	0.4326	23.7992	1.7427
Observations: 39						

This table reports statistics for some important variables used in the Merton-KMV model and the logit model. *E* is the market value of firm's equity in million RMB as the product of share price and the number of share outstanding. *F* is the face value of firm's debt in million RMB as the product of short-term debt and 50% of long-term debt. σ_E is the annualized volatility of the firm's equity measured by former two years' monthly data. Colum (4) to column (6) report three financial ratios, saying net income over book value of total assets (*NITA*), total liability over total asset (*TLTA*), and liquid asset over short-term liability (*LASTL*). All the data are obtained from the database *iFind*. Due to the data availability, only 39 defaults are included in our sample.

6. Empirical results

6.1 Calculation results from the Merton-KMV model

We computer the "Default Likelihood Indicators" (*DLI*) for our whole sample and list the results in this section. Table 6.1.1 report the aggregate *DLI* per year from 2000 to 2010 and the annual number of observations included in our sample. The aggregate *DLI* is defined as a simple average of the *DLI* of all firms. As it is argued by Tudela & Young (2005) that in principal, the aggregate *DLI* should be a useful indictor of the overall default rate (Tudela & Young, 2005).

Table 6.1.1 Aggregate *DLI* by Year from 2000 to 2010

Year	Observations	Aggregate *DLI*
2001	487	0.0003200
2002	547	0.0003883
2003	626	0.0017722
2004	657	0.0065944
2005	662	0.0058577
2006	711	0.0039594
2007	705	0.0000969
2008	737	0.0256091
2009	821	0.0065789
2010	864	0.0002000

This table reports the aggregate "Default Likelihood Indicators" (*DLI*) by year from 2000 to 2010. The aggregate *DLI* is defined as the simple average of the *DLI* of all firms.

Table 6.1.1 reveals that the "default probability" is not high for Chinese listed firms[26] but it is increasing year after year. The first dramatic increase is found in 2004 before China implements *Share Merger Reforms*. Since *DLI* here is a one-year-ahead default predictive indicator, high aggregate *DLI* in 2004 implies that in general the *Share Merger Reforms* in 2005 is expected to accelerate the default of the problematic firms

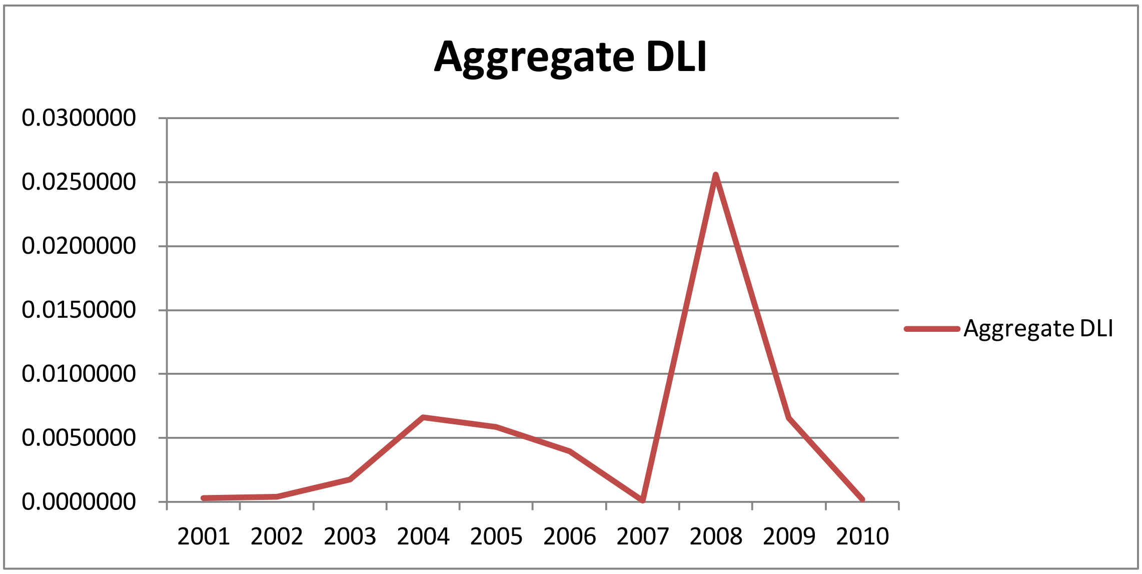
[26] We compare our results with those calculated by using Anglo-American market data and find that generally the "default probability" is not high for Chinese listed firms. For example, Vassalou & Xing (2004) figured the monthly aggregate DLI for American listed firms from 1971 to 1998 and revealed that most of the monthly aggregate DLI are above 0.0202.

which used to cover the “bad news”. Recalling table 5.1, which reveals that the number of defaults increases in 2005, we feel that *DLI* is probably a powerful indicator of defaults. We will test the significance of the *DLI* in forecasting defaults later.

In addition, there is a huge decrease in 2007, when the new Enterprise Bankruptcy Law became effective. It seems that the new Enterprise Bankruptcy Law is expected to have a positive effect in Chinese market, however further studies are needed.

Finally the highest aggregate *DLI* is found in 2008 when financial crisis reached its fever pitch (figure 6.1.1 gives a much clearer overview). Although we reported in table 5.1 that in total there are no firms defaulted in 2008, the aggregate *DLI* is extremely high in this year.

Figure 6.1.1 Aggregate *DLI* by Year from 2000 to 2010



The aggregate *DLI* is defined as the simple average of the *DLI* of all firms.

Table 6.1.2 present the summary statistics of the “Default Likelihood Indicators” (*DLI*) for both defaulted firms and surviving firms. It is showed in table 6.1.2 that defaulted group has both larger maximum *DLI* and minimum *DLI* than surviving group. And not surprisingly, the mean value of *DLI* for defaulted group is much higher than that for the surviving group. This finding implies that if we set an appropriate threshold, for example, 10%, "Default Likelihood Indicators" (*DLI*) may be a useful indicator to discrepant defaulted firms from surviving firms.

Table 6.1.2 Comparison of *DLI* between Defaulted Firms and Surviving Firms

Group	Obs.	Mean	Std. Dev.	Min	Max
Defaulted Firms	39	0.095675	0.186856	6.71E-10	1
Surviving Firms	7218	0.004617	0.020508	0	0.535457

This table reports statistics for "Default Likelihood Indicators" (DLI) calculated from the Merton-KMV model from 2000 to 2010.

We report the Type I, cases that the Merton-KMV model fails to predict default when it did occur, and Type II errors, where the Merton-KMV model predicts default when it did not occur, for different thresholds in table 6.1.3. Since the aggregate *DLI* is generally quite small for Chinese listed firms, we include two extremely low levels of threshold in table 6.1.3, respectively 0.01% and 0.1%.

Table 6.1.3 Type I & II Errors for Different Thresholds

Threshold	Type I	Type II
0.01%	17.95%	25.92%
0.10%	30.77%	17.58%
1%	51.28%	8.63%
5%	61.54%	2.76%
10%	71.79%	0.83%
15%	79.49%	0.39%
20%	84.62%	0.14%
25%	89.74%	0.07%
30%	92.31%	0.06%
40%	94.87%	0.04%
50%	97.44%	0.01%

Table 6.1.3 shows Type I & II errors for different thresholds for our whole sample. Type I error is the proportion of companies that the Merton-KMV model fails to predict default when it did occur and Type II errors is the proportion of companies that are classified as defaulted when they are not.

It is quit intuitive that the lower the threshold the smaller the Type I error but at the expense of a greater Type II error. For example, choosing a failure threshold of 0.01%, we fail to classify 17.95% of firms as defaulters when they actually went default. At this level, the Type II error is 25.92%. With the higher level of 1%, the Type one error increases to 51.28% while Type II error decreases to 8.63%. As it is argued by Tudela & Young (2005) that in reality the proper threshold is depend on the preference of the investors (Tudela & Young, 2005).

6.2 The regression results

We stated in section 4 that in order to 1) evaluate the significance of the Merton-KMV model; 2) compare the information content of the *DLI* and financial ratios; 3) test the contribution of the functional form used by the Merton-KMV model, we construct logit models using an indicator of default as a dependent variable. The indicator of default is a dummy variable which takes on the value of unity if the firm were delisted for financial reasons, and zero otherwise.

We first regress the dummy variables on *DLI* to see if *DLI* is a useful and sufficient indicator to predict default for Chinese listed companies. If the coefficient of the *DLI* is significantly different from zero, we can demonstrate that *DLI* is a useful variable to predict default; otherwise we can conclude that the Merton-KMV model is not an appropriate way to forecast default in Chinese market.

In addition, to compare the information content of the *DLI* and financial ratios, we included *DLI* as well as financial ratios that are statistically significant in predicting default in the regression. If *DLI* is the only one that is statistically significant, we can conclude that *DLI* is a sufficient statistic for predicting default and all the useful information contained in the financial ratios are included in the Merton-KMV model. Before doing this test, we have to identify the information content of the accounting ratios.

Finally we examine whether the functional form of the Merton-KMV model add value to that provided by its components. To test this hypothesis, we use *DLI* as well as the important components of the Merton-KMV model in the regression. If the *DLI* remains statistically significant, we can say that the functional form of the Merton-KMV is an important construct for forecast default in Chinese market. The specific regression models are listed as following.

Model 1

$$P_{t-1}(Y_{i,t} = 1) = \frac{exp(\alpha + \beta_0 DLI_{i,t-1} + \varepsilon_{i,t-1})}{1 + exp(\alpha + \beta_0 DLI_{i,t-1} + +\varepsilon_{i,t-1})}$$

Model 2

$$P_{t-1}(Y_{i,t} = 1) = \frac{\exp(\alpha + \beta_1 NINA_{i,t-1} + \beta_2 TLTA_{i,t-1} + \beta_3 LASTL_{i,t-1} + \varepsilon_{i,t-1})}{1 + exp(\alpha + \beta_1 NINA_{i,t-1} + \beta_2 TLTA_{i,t-1} + \beta_3 LASTL_{i,t-1} + \varepsilon_{i,t-1})}$$

Model 3

$$P_{t-1}(Y_{i,t} = 1) = \frac{\exp(\alpha + \beta_0 DLI_{i,t-1} + \beta_1 NINA_{i,t-1} + \beta_2 TLTA_{i,t-1} + \beta_3 LASTL_{i,t-1} + \varepsilon_{i,t-1})}{1 + exp(\alpha + \beta_0 DLI_{i,t-1} + \beta_1 NINA_{i,t-1} + \beta_2 TLTA_{i,t-1} + \beta_3 LASTL_{i,t-1} + \varepsilon_{i,t-1})}$$

Model 4

$$P_{t-1}(Y_{i,t} = 1) = \frac{\exp\left(\alpha + \beta_0 DLI_{i,t-1} + \beta_4 lnE_{i,t-1} + \beta_5 lnF_{i,t-1} + \beta_6 1/\sigma_{E_{i,t-1}} + \varepsilon_{i,t-1}\right)}{1 + exp\left(\alpha + \beta_0 DLI_{i,t-1} + \beta_4 lnE_{i,t-1} + \beta_5 lnF_{i,t-1} + \beta_6 1/\sigma_{E_{i,t-1}} + \varepsilon_{i,t-1}\right)}$$

The regression results are reported in table 6.2.1. Model in column 1 is a univariate model which obtains *DLI* as the only independent variable. The result shows that the covariate is statistically significant at 0.1% level, allowing us to conclude that the *DLI* is an extremely significant default predictor.

The model in column 2 is an accounting model that uses financial ratios as independent variables. The results reveal that all of the three financial ratios are statistically significant with the expected sign. Our findings are similar to those of Campbell et al.(2008), which reveal that the ratio of Net Income to Total Assets (*NINA*), total liabilities relative to total assets (*TLTA*) and the ratio of a company's cash and short-term assets to the market value of its assets (*CASHTA*), another way to measure liquidity, are statistically significant in predicting default. With these findings we can continue to test hypothesis 2. Since all the three financial ratios are statistically significant, we will combine all of them with *DLI* as the independent variables in the regression to see if we can improve on the Merton-KMV model's implied *DLI* for forecasting.

Model 3 adds *DLI*, in conjunction with the financial ratios measuring profitability, leverage and liquidity. The results in column 3 reveal that the coefficients of the *DLI* and the financial ratios are very statistically significant. This finding allows us to conclude that we can improve the predictive power of the Merton-KMV model by adding financial ratios that measuring profitability, leverage and liquidity. In other words we can reject our second hypothesis and conclude that the *DLI* is not a sufficient statistic for default forecasting because.

The model in column 4 contains the *DLI* and the main components of the Merton-KMV model: the log of the firm's equity value, the log of the firm's debt and the inverse of the firm's equity volatility. It is found that the *DLI* remains statistically significant compare with that in model 1, although its coefficient dropped by approximately 50%. In addition, the log of the firm's equity value and the log of the firm's debt are also statistically significant with the expected sign. The results in column 4 allow us to conclude that the functional form of the Merton-KMV model is as important as the inputs of the Merton-KMV model in predicting default.

To sum up, table 6.2.1 reveals that the Merton-KMV is a significant method to predict default in Chinese market, however it is not a sufficient method. In other words, we can improve the predictive performance of the Merton-KMV model by adding financial ratios measuring profitability, leverage and liquidity. Finally we find that the functional form of the Merton-KMV model adds value to that of the inputs for this model.

Table 6.2.1 Regression Results

	Model 1	Model 2	Model 3	Model 4
DLI	15.29^{***}		7.361^{***}	6.810^{**}
	(7.75)		(3.80)	(2.63)
NINA		-3.423^{***}	-3.151^{***}	
		(-5.36)	(-4.94)	
TLTA		0.173^{*}	0.188^{*}	
		(1.97)	(2.20)	
LASTL		-4.086^{***}	-3.606^{***}	
		(-5.73)	(-4.96)	
lnE				-2.344^{***}
				(-8.31)
lnF				-0.259
				(-1.25)
$1/\sigma_E$				-0.683^{*}
				(-2.43)
_cons	-5.529^{***}	-2.537^{***}	-3.065^{***}	2.320^{**}
	(-30.18)	(-5.59)	(-6.12)	(2.59)
N	7257	7257	7257	7257

Table 6.2.1 reports the estimated coefficients and the *t*-statistics in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. *DLI* is the implied "Default Likelihood Indicators". *NINA* is the ratio of Net Income to Total Assets. *TLTA* is the total liabilities relative to total assets. *LASTA* is the ratio of a company's liquid assets to its short-term liability. *lnE* is the log of the firm's equity value. *lnF* is the log of the firm's debt. $1/\sigma_E$ is the inverse of the firm's equity volatility.

6.3 Power curve

Referring to Tudela & Young (2005), we now in this section evaluate the ability of the Merton-KMM model and other two different models to rank defaulted firms and surviving firms using power curve. From the regressions above, we can construct an accounting model that includes pure financial ratios and a hybrid model that is a mix of *DLI* and financial ratios, which are listed as follows:

Accounting model

$$P_{t-1}(Y_{i,t} = 1)$$
$$= \frac{\exp(-2.537 - 3.423 * NINA_{i,t-1} + 0.173 * TLTA_{i,t-1} - 4.086 * LASTL_{i,t-1})}{1 + exp(-2.537 - 3.423 * NINA_{i,t-1} + 0.173 * TLTA_{i,t-1} - 4.086 * LASTL_{i,t-1})}$$

Hybrid model

$$P_{t-1}(Y_{i,t} = 1) =$$

$$\frac{\exp(-3.065 - 7.361 * DLI_{i,t-1} - 3.151 * NINA_{i,t-1} + 0.188 * TLTA_{i,t-1} - 3.606 * LASTL_{i,t-1})}{1 + exp(-3.065 - 7.361 * DLI_{i,t-1} - 3.151 * NINA_{i,t-1} + 0.188 * TLTA_{i,t-1} * -3.606 * LASTL_{i,t-1})}$$

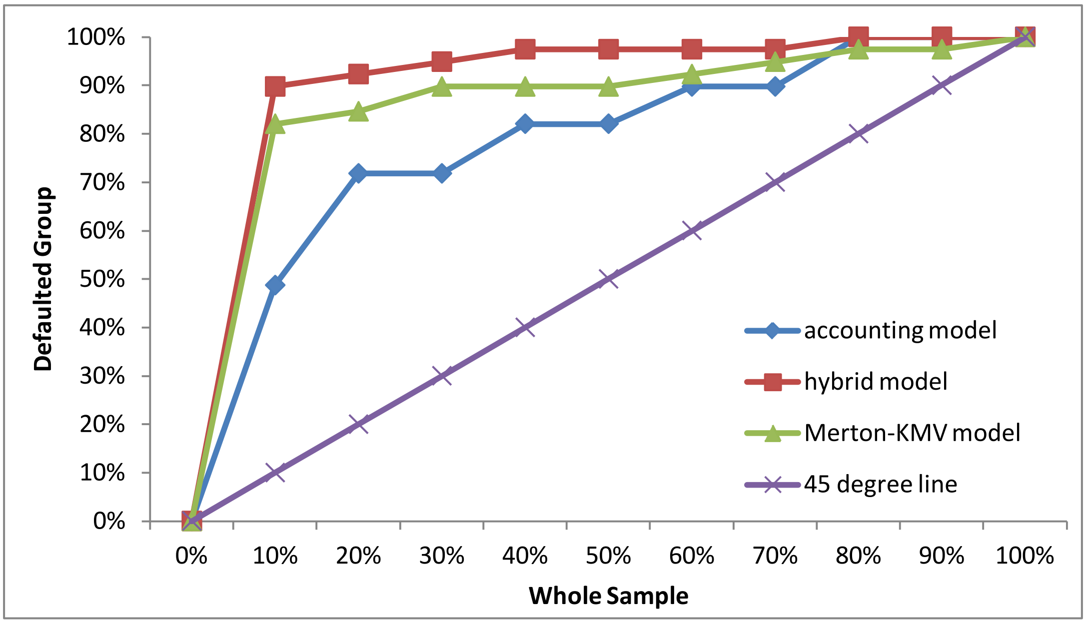
First we calculated the probability of default (P_{t-1}) for our whole sample using the model. We then rank the companies by probability of default from the highest to lowest along the horizon axis. Next, for a given percentage of this sample we calculate the cumulative number of defaulters picked up by the model as a proportion of the total number of defaulted firms in our sample, and plot the cumulative proportion on the vertical axis.

As it is described by Tudela & Young (2005) that plotting the power curve for a random model will give us a 45 degree line since intuitively a random model will pick up 1% of the total defaults for the first percentile while for the most powerful model, all the defaulters should be included within the riskiest percentile. In other words, the better the model in predicting defaults, the more bowed towards the upper-left corner its power curve will be.

The power curves for the Merton-KMV model, the accounting model and the hybrid model are plotted in figure 6.3.1. Since all the power curves are plotted by using the same sample, we can compare the power of the three different models.

Figure 6.3.1 shows that the hybrid model outperforms both the Merton-KMV model and the pure accounting model, indicating that a combination of the *DLI* and financial ratios measuring profitability, leverage and liquidity does add value to that of the Merton-KMV model.

Figure 6.3.1 Power Curve



The vertical axis is the percentiles for the whole sample rating from the riskiest firms to the safest firms while horizontal axis is the cumulative ratio of the number of defaulter within this percentile to the total number of defaulter in our sample.

In addition, the Merton-KMV model performs better than accounting data. As it is argued by Vassalou & Xing (2004) that the reasons might be: 1) the volatility of the firm's assets contains important information about the firm's default risk, however accounting models do not take into account the volatility of the firm's assets in estimating its default risk as the Merton-KMV model does; 2) accounting models use the accounting data from historical financial statement which is inherently backward looking while the Merton-KMV model applies the market value of the firm's equity, which reflects the expectation of the firm's future performance.

7. Conclusions

The main purposes of this paper are: 1) calculate the “Default Likelihood Indicators” (*DLI*) of the Chinese listed firms by using the Merton-KMV model; 2) estimate the whether we can improve the predictive power of Merton-KMV model by adding some financial ratios measuring profitability, leverage and liquidity; 3) test whether the functional form of the Merton-KMV model adds value to that of the inputs for the model.

Including 7,257 observations from 2000 to 2010 in our sample, we find that the annual aggregate “Default Likelihood Indicators” (*DLI*) for Chinese listed companies is lower than that of the Anglo-American firms.

To test whether the Merton-KMV model is a significant and sufficient method in predict default in Chinese market, we construct some econometric models. The regression results reveal that the Merton-KMV is a significant method to predict default in Chinese market but it is not a sufficient method. We can improve the predictive performance of the Merton-KMV model by adding financial ratios measuring profitability, leverage and liquidity in the econometric model. In addition, Merton-KMV model is significant in predicting default not only because that some of the inputs are useful, but also because that the functional form of the Merton-KMV model adds value to that of the inputs for the model.

Finally we draw the power curve for the Merton-KMV model, the pure accounting model and a hybrid model that combine *DLI* calculated from the Merton-KMV model and financial ratios measuring profitability, leverage and liquidity. We find that hybrid model outperforms the other two models and the accounting model is the weakest one. The finding proves what we revealed, saying we can improve the Merton-KMV model by adding accounting data.

Some **limitations** are remained in this paper. First, some of the assumptions may be too strong. For example, we assume that the firm's asset follows geometric Brownian motion. This may be violated in the reality. Applying the KMV's proprietary database that translate the "Distance to Default" (*DD*) of the firm to the "Expected Default Frequency" (*EDF*) can solve this problem, however this database is not available for public use and it may not suitable for Chinese firms since it is based on the observations of America firms. Second, our results may be biased due to the insufficiency of defaults included in our studies. The problem of data insufficiency is always a problem for researcher who wants to study Chinese market due to the China's special institutional environment.

There are several areas for future research. One extension of the paper is to explore how the special institutional background shapes various corporate behaviors. We mentioned in section 5 that the aggregate *DLI* increases in 2004 before China implements the *Share Merger Reforms*. We think it is because Chinese listed firms tend to cover "bad news" and the *Share Merger Reforms* enforce them to convey all the information to the public thus the "bad news" that used to be under ground is now converged into the price. This implication needs to be proved by further studies. In addition, there is a huge decrease in 2007, when the new Enterprise Bankruptcy Law became effective. It seems that the new Enterprise Bankruptcy Law is expected to have a positive effect in Chinese market, still further studies are needed. Second, we describe in section 2 that there is another branch of models based on bond market and the Merton-KMV model tends to outperforms bond market based models. However we do not unfolded this topic in our study. Further studies are encouraged to compare these two types of models and test whether we can improve the predictive power of the Merton-KMV model by combining data from both equity market and bond market.

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